

```

import numpy as np
import pandas as pd

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error, mean_absolute_error,
r2_score

import keras

from keras.models import Sequential
from keras.layers import Dense

boston =
pd.read_csv("C:/Users/user/OneDrive/Documents/boston_house_prices.csv"
)

X = boston[['LSTAT', 'RM', 'PTRATIO']]
y = boston['PRICE']

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=4)

scaler = StandardScaler()

X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

lr_model = LinearRegression()

lr_model.fit(X_train_scaled, y_train)

LinearRegression()

y_pred_lr = lr_model.predict(X_test_scaled)

mse_lr = mean_squared_error(y_test, y_pred_lr)
mae_lr = mean_absolute_error(y_test, y_pred_lr)
r2_lr = r2_score(y_test, y_pred_lr)

print("Linear Regression Model Evaluation:")
print(f"Mean Squared Error: {mse_lr}")
print(f"Mean Absolute Error: {mae_lr}")
print(f"R2 Score: {r2_lr}")

Linear Regression Model Evaluation:
Mean Squared Error: 30.340105190234596

```

Mean Absolute Error: 3.5844321029226935
R2 Score: 0.6733732528519258

```
model = Sequential([
    Dense(128, activation='relu', input_dim=3),
    Dense(64, activation='relu'), # Second hidden layer with 64 neurons
    Dense(32, activation='relu'), # Third hidden layer with 32 neurons
    Dense(16, activation='relu'), # Fourth hidden layer with 16 neurons
    Dense(1) # Output layer (Predicting a single value - House Price)
])
```

C:\Users\user\AppData\Local\Programs\Python\Python312\Lib\site-packages\keras\src\layers\core\dense.py:87: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.

```
    super().__init__(activity_regularizer=activity_regularizer,
**kwargs)
```

```
model.compile(optimizer='adam', loss='mse', metrics=['mae'])
```

```
history = model.fit(X_train_scaled, y_train, epochs=100,
validation_split=0.05,
verbose=1)
```

Epoch 1/100

12/12 _____ 3s 40ms/step - loss: 558.4482 - mae: 21.9765 - val_loss: 450.3156 - val_mae: 20.2921

Epoch 2/100

12/12 _____ 0s 14ms/step - loss: 536.5029 - mae: 21.5812 - val_loss: 416.3425 - val_mae: 19.4733

Epoch 3/100

12/12 _____ 0s 16ms/step - loss: 482.1914 - mae: 20.3584 - val_loss: 342.8159 - val_mae: 17.5320

Epoch 4/100

12/12 _____ 0s 15ms/step - loss: 363.1593 - mae: 17.3251 - val_loss: 205.3314 - val_mae: 13.5232

Epoch 5/100

12/12 _____ 0s 13ms/step - loss: 165.9587 - mae: 11.4851 - val_loss: 77.0294 - val_mae: 7.5972

Epoch 6/100

12/12 _____ 0s 12ms/step - loss: 85.3024 - mae: 7.2307 - val_loss: 52.3408 - val_mae: 5.5998

Epoch 7/100

12/12 _____ 0s 15ms/step - loss: 58.2356 - mae: 5.8537 - val_loss: 34.4172 - val_mae: 4.8382

Epoch 8/100

12/12 _____ 0s 12ms/step - loss: 45.4778 - mae: 5.1046 - val_loss: 25.7385 - val_mae: 3.8787

Epoch 9/100

```
12/12 _____ 0s 12ms/step - loss: 38.6701 - mae: 4.4921
- val_loss: 23.7786 - val_mae: 3.5410
Epoch 10/100
12/12 _____ 0s 11ms/step - loss: 35.6649 - mae: 4.2899
- val_loss: 20.5281 - val_mae: 3.3900
Epoch 11/100
12/12 _____ 0s 11ms/step - loss: 23.1289 - mae: 3.5482
- val_loss: 19.1803 - val_mae: 3.3118
Epoch 12/100
12/12 _____ 0s 11ms/step - loss: 24.6844 - mae: 3.4120
- val_loss: 19.1009 - val_mae: 3.2690
Epoch 13/100
12/12 _____ 0s 15ms/step - loss: 24.3774 - mae: 3.6290
- val_loss: 18.1436 - val_mae: 3.1857
Epoch 14/100
12/12 _____ 0s 11ms/step - loss: 22.7329 - mae: 3.5506
- val_loss: 15.7544 - val_mae: 3.0156
Epoch 15/100
12/12 _____ 0s 10ms/step - loss: 20.8309 - mae: 3.2806
- val_loss: 16.6806 - val_mae: 3.0508
Epoch 16/100
12/12 _____ 0s 10ms/step - loss: 32.0213 - mae: 3.7996
- val_loss: 14.8839 - val_mae: 2.9093
Epoch 17/100
12/12 _____ 0s 11ms/step - loss: 22.6907 - mae: 3.4277
- val_loss: 14.1685 - val_mae: 2.8388
Epoch 18/100
12/12 _____ 0s 10ms/step - loss: 22.0470 - mae: 3.4952
- val_loss: 14.6247 - val_mae: 2.8339
Epoch 19/100
12/12 _____ 0s 14ms/step - loss: 26.4218 - mae: 3.4816
- val_loss: 13.7802 - val_mae: 2.7950
Epoch 20/100
12/12 _____ 0s 11ms/step - loss: 19.5107 - mae: 3.1484
- val_loss: 13.3523 - val_mae: 2.7413
Epoch 21/100
12/12 _____ 0s 11ms/step - loss: 22.8199 - mae: 3.3039
- val_loss: 12.0844 - val_mae: 2.6618
Epoch 22/100
12/12 _____ 0s 10ms/step - loss: 23.9024 - mae: 3.4688
- val_loss: 11.9909 - val_mae: 2.6362
Epoch 23/100
12/12 _____ 0s 11ms/step - loss: 22.1655 - mae: 3.3527
- val_loss: 11.9177 - val_mae: 2.6208
Epoch 24/100
12/12 _____ 0s 11ms/step - loss: 25.3433 - mae: 3.3624
- val_loss: 11.0400 - val_mae: 2.5641
Epoch 25/100
12/12 _____ 0s 14ms/step - loss: 16.5975 - mae: 2.9739
```

```
- val_loss: 11.5640 - val_mae: 2.6140
Epoch 26/100
12/12 _____ 0s 12ms/step - loss: 20.8914 - mae: 3.2004
- val_loss: 10.6741 - val_mae: 2.5551
Epoch 27/100
12/12 _____ 0s 11ms/step - loss: 19.4663 - mae: 3.0185
- val_loss: 10.5644 - val_mae: 2.5511
Epoch 28/100
12/12 _____ 0s 10ms/step - loss: 21.3041 - mae: 3.2038
- val_loss: 10.6064 - val_mae: 2.5581
Epoch 29/100
12/12 _____ 0s 11ms/step - loss: 14.3716 - mae: 2.8109
- val_loss: 10.1869 - val_mae: 2.5205
Epoch 30/100
12/12 _____ 0s 11ms/step - loss: 18.8920 - mae: 2.9652
- val_loss: 10.2464 - val_mae: 2.5621
Epoch 31/100
12/12 _____ 0s 14ms/step - loss: 15.0054 - mae: 2.8159
- val_loss: 8.9708 - val_mae: 2.4330
Epoch 32/100
12/12 _____ 0s 11ms/step - loss: 21.1460 - mae: 2.9708
- val_loss: 9.5060 - val_mae: 2.5282
Epoch 33/100
12/12 _____ 0s 12ms/step - loss: 18.9033 - mae: 3.0201
- val_loss: 9.2572 - val_mae: 2.5264
Epoch 34/100
12/12 _____ 0s 20ms/step - loss: 14.3942 - mae: 2.7257
- val_loss: 9.5576 - val_mae: 2.5723
Epoch 35/100
12/12 _____ 0s 11ms/step - loss: 15.5148 - mae: 2.7906
- val_loss: 8.3091 - val_mae: 2.4390
Epoch 36/100
12/12 _____ 0s 17ms/step - loss: 13.4832 - mae: 2.7081
- val_loss: 8.9944 - val_mae: 2.5499
Epoch 37/100
12/12 _____ 0s 11ms/step - loss: 15.7622 - mae: 2.7967
- val_loss: 8.7568 - val_mae: 2.5487
Epoch 38/100
12/12 _____ 0s 11ms/step - loss: 16.4898 - mae: 2.8297
- val_loss: 7.3973 - val_mae: 2.3749
Epoch 39/100
12/12 _____ 0s 11ms/step - loss: 22.5962 - mae: 2.9413
- val_loss: 9.3802 - val_mae: 2.6521
Epoch 40/100
12/12 _____ 0s 11ms/step - loss: 18.5410 - mae: 2.7552
- val_loss: 7.4738 - val_mae: 2.4232
Epoch 41/100
12/12 _____ 0s 11ms/step - loss: 14.5337 - mae: 2.5922
- val_loss: 9.0476 - val_mae: 2.6334
```

```
Epoch 42/100
12/12 _____ 0s 13ms/step - loss: 15.2319 - mae: 2.7152
- val_loss: 8.4537 - val_mae: 2.5722
Epoch 43/100
12/12 _____ 0s 16ms/step - loss: 15.4697 - mae: 2.7502
- val_loss: 8.9087 - val_mae: 2.6518
Epoch 44/100
12/12 _____ 0s 12ms/step - loss: 16.0910 - mae: 2.7191
- val_loss: 7.8612 - val_mae: 2.5029
Epoch 45/100
12/12 _____ 0s 12ms/step - loss: 15.7386 - mae: 2.6747
- val_loss: 7.5770 - val_mae: 2.4403
Epoch 46/100
12/12 _____ 0s 11ms/step - loss: 12.9910 - mae: 2.5354
- val_loss: 9.4161 - val_mae: 2.7146
Epoch 47/100
12/12 _____ 0s 13ms/step - loss: 12.3924 - mae: 2.5452
- val_loss: 7.6284 - val_mae: 2.4750
Epoch 48/100
12/12 _____ 0s 11ms/step - loss: 17.4669 - mae: 2.6737
- val_loss: 7.9148 - val_mae: 2.4950
Epoch 49/100
12/12 _____ 0s 16ms/step - loss: 16.6065 - mae: 2.7352
- val_loss: 7.7811 - val_mae: 2.4951
Epoch 50/100
12/12 _____ 0s 11ms/step - loss: 12.0027 - mae: 2.4045
- val_loss: 8.8266 - val_mae: 2.6822
Epoch 51/100
12/12 _____ 0s 11ms/step - loss: 12.1055 - mae: 2.4475
- val_loss: 8.6357 - val_mae: 2.6090
Epoch 52/100
12/12 _____ 0s 15ms/step - loss: 15.2651 - mae: 2.5277
- val_loss: 7.6060 - val_mae: 2.5005
Epoch 53/100
12/12 _____ 0s 11ms/step - loss: 18.3341 - mae: 2.8797
- val_loss: 7.5191 - val_mae: 2.4518
Epoch 54/100
12/12 _____ 0s 13ms/step - loss: 19.0331 - mae: 2.7544
- val_loss: 8.1436 - val_mae: 2.5669
Epoch 55/100
12/12 _____ 0s 11ms/step - loss: 15.5007 - mae: 2.6438
- val_loss: 7.4917 - val_mae: 2.4371
Epoch 56/100
12/12 _____ 0s 11ms/step - loss: 13.7857 - mae: 2.5769
- val_loss: 7.6259 - val_mae: 2.4645
Epoch 57/100
12/12 _____ 0s 11ms/step - loss: 11.5134 - mae: 2.3889
- val_loss: 8.2004 - val_mae: 2.5702
Epoch 58/100
```

```
12/12 _____ 0s 21ms/step - loss: 16.6562 - mae: 2.6365
- val_loss: 7.1165 - val_mae: 2.3957
Epoch 59/100
12/12 _____ 0s 24ms/step - loss: 13.7722 - mae: 2.5540
- val_loss: 9.1009 - val_mae: 2.6669
Epoch 60/100
12/12 _____ 0s 11ms/step - loss: 12.5757 - mae: 2.5470
- val_loss: 7.7798 - val_mae: 2.4966
Epoch 61/100
12/12 _____ 0s 14ms/step - loss: 12.9680 - mae: 2.4211
- val_loss: 7.9209 - val_mae: 2.5134
Epoch 62/100
12/12 _____ 0s 16ms/step - loss: 13.9734 - mae: 2.5404
- val_loss: 8.4276 - val_mae: 2.5904
Epoch 63/100
12/12 _____ 0s 15ms/step - loss: 18.2426 - mae: 2.6518
- val_loss: 8.2447 - val_mae: 2.5613
Epoch 64/100
12/12 _____ 0s 12ms/step - loss: 10.8237 - mae: 2.4207
- val_loss: 7.6747 - val_mae: 2.4706
Epoch 65/100
12/12 _____ 0s 11ms/step - loss: 12.5759 - mae: 2.4939
- val_loss: 8.2119 - val_mae: 2.5203
Epoch 66/100
12/12 _____ 0s 13ms/step - loss: 13.6622 - mae: 2.4833
- val_loss: 7.8100 - val_mae: 2.4949
Epoch 67/100
12/12 _____ 0s 11ms/step - loss: 18.2152 - mae: 2.7145
- val_loss: 6.8533 - val_mae: 2.3006
Epoch 68/100
12/12 _____ 0s 11ms/step - loss: 13.1264 - mae: 2.4457
- val_loss: 8.2580 - val_mae: 2.5471
Epoch 69/100
12/12 _____ 0s 16ms/step - loss: 12.1755 - mae: 2.4503
- val_loss: 7.4530 - val_mae: 2.4022
Epoch 70/100
12/12 _____ 0s 12ms/step - loss: 15.6821 - mae: 2.5396
- val_loss: 8.5331 - val_mae: 2.5924
Epoch 71/100
12/12 _____ 1s 32ms/step - loss: 13.6082 - mae: 2.4964
- val_loss: 7.2110 - val_mae: 2.3592
Epoch 72/100
12/12 _____ 1s 23ms/step - loss: 14.2540 - mae: 2.5940
- val_loss: 7.7783 - val_mae: 2.4527
Epoch 73/100
12/12 _____ 0s 12ms/step - loss: 14.6654 - mae: 2.5533
- val_loss: 8.0091 - val_mae: 2.5127
Epoch 74/100
12/12 _____ 0s 12ms/step - loss: 13.8118 - mae: 2.5000
```

```
- val_loss: 9.0584 - val_mae: 2.5919
Epoch 75/100
12/12 _____ 0s 12ms/step - loss: 12.6933 - mae: 2.4954
- val_loss: 7.5925 - val_mae: 2.4651
Epoch 76/100
12/12 _____ 0s 19ms/step - loss: 13.3243 - mae: 2.4767
- val_loss: 6.8478 - val_mae: 2.2868
Epoch 77/100
12/12 _____ 0s 17ms/step - loss: 11.7061 - mae: 2.4485
- val_loss: 9.8217 - val_mae: 2.7066
Epoch 78/100
12/12 _____ 0s 15ms/step - loss: 16.1263 - mae: 2.6948
- val_loss: 6.8323 - val_mae: 2.2623
Epoch 79/100
12/12 _____ 0s 12ms/step - loss: 13.7347 - mae: 2.4986
- val_loss: 8.6645 - val_mae: 2.5773
Epoch 80/100
12/12 _____ 1s 72ms/step - loss: 13.9701 - mae: 2.4583
- val_loss: 8.3102 - val_mae: 2.4387
Epoch 81/100
12/12 _____ 0s 19ms/step - loss: 16.5333 - mae: 2.6865
- val_loss: 7.3207 - val_mae: 2.3690
Epoch 82/100
12/12 _____ 0s 21ms/step - loss: 10.9457 - mae: 2.3682
- val_loss: 11.0929 - val_mae: 2.8025
Epoch 83/100
12/12 _____ 0s 25ms/step - loss: 13.8954 - mae: 2.5281
- val_loss: 6.9698 - val_mae: 2.2528
Epoch 84/100
12/12 _____ 0s 16ms/step - loss: 11.6310 - mae: 2.3676
- val_loss: 8.7259 - val_mae: 2.5682
Epoch 85/100
12/12 _____ 0s 19ms/step - loss: 17.5628 - mae: 2.6716
- val_loss: 9.1160 - val_mae: 2.5737
Epoch 86/100
12/12 _____ 0s 11ms/step - loss: 10.1486 - mae: 2.4025
- val_loss: 8.0717 - val_mae: 2.4797
Epoch 87/100
12/12 _____ 0s 16ms/step - loss: 12.5134 - mae: 2.4687
- val_loss: 8.8722 - val_mae: 2.5176
Epoch 88/100
12/12 _____ 0s 12ms/step - loss: 13.6216 - mae: 2.6657
- val_loss: 8.0997 - val_mae: 2.4470
Epoch 89/100
12/12 _____ 0s 12ms/step - loss: 15.3951 - mae: 2.5530
- val_loss: 7.0846 - val_mae: 2.3432
Epoch 90/100
12/12 _____ 0s 15ms/step - loss: 13.2596 - mae: 2.3998
- val_loss: 7.8280 - val_mae: 2.3938
```

```

Epoch 91/100
12/12 _____ 0s 13ms/step - loss: 10.3848 - mae: 2.3366
- val_loss: 8.7327 - val_mae: 2.5531
Epoch 92/100
12/12 _____ 0s 18ms/step - loss: 13.3991 - mae: 2.4545
- val_loss: 8.8516 - val_mae: 2.5468
Epoch 93/100
12/12 _____ 0s 13ms/step - loss: 16.0399 - mae: 2.6286
- val_loss: 6.9360 - val_mae: 2.2814
Epoch 94/100
12/12 _____ 0s 17ms/step - loss: 11.1777 - mae: 2.4042
- val_loss: 8.9790 - val_mae: 2.5348
Epoch 95/100
12/12 _____ 0s 17ms/step - loss: 11.2329 - mae: 2.3451
- val_loss: 8.5491 - val_mae: 2.5203
Epoch 96/100
12/12 _____ 0s 11ms/step - loss: 14.1890 - mae: 2.5583
- val_loss: 7.4756 - val_mae: 2.3152
Epoch 97/100
12/12 _____ 0s 17ms/step - loss: 16.8445 - mae: 2.5515
- val_loss: 8.6353 - val_mae: 2.5320
Epoch 98/100
12/12 _____ 0s 14ms/step - loss: 19.1422 - mae: 2.7137
- val_loss: 6.7421 - val_mae: 2.2036
Epoch 99/100
12/12 _____ 0s 12ms/step - loss: 16.0599 - mae: 2.4967
- val_loss: 8.6231 - val_mae: 2.5285
Epoch 100/100
12/12 _____ 0s 10ms/step - loss: 10.4781 - mae: 2.3709
- val_loss: 9.4234 - val_mae: 2.5692

y_pred_nn = model.predict(X_test_scaled) # Predicting house prices on
test data
mse_nn, mae_nn = model.evaluate(X_test_scaled, y_test)

4/4 _____ 0s 17ms/step
4/4 _____ 0s 18ms/step - loss: 17.8093 - mae: 2.6942

print("\nNeural Network Model Evaluation:")
print(f"Mean Squared Error: {mse_nn}")
print(f"Mean Absolute Error: {mae_nn}")

Neural Network Model Evaluation:
Mean Squared Error: 22.3957462310791
Mean Absolute Error: 2.870593547821045

new_data = np.array([[0.1, 10.0, 5.0]])
new_data_scaled = scaler.transform(new_data)

```



```
C:\Users\user\AppData\Local\Programs\Python\Python312\Lib\site-packages\sklearn\base.py:493: UserWarning: X does not have valid feature names, but StandardScaler was fitted with feature names
  warnings.warn(
```

```
prediction = model.predict(new_data_scaled)
```

```
1/1 ————— 0s 243ms/step
```

```
print("\nPredicted House Price:", prediction[0][0])
```

```
Predicted House Price: 80.68836
```